- 2005: The appearance of the first web site for automatic translation ,like Google (http://translate.google.fr/).
- 2007: METIS-II is a hybrid machine translation system, in which insights from Statistical, Example based, and Rule-based Machine Translation (SMT, EBMT, and RBMT respectively) are used.
- 2008 : 23% of internet users, have used the machine translation and 40 % considering doing so
- 2009: 30% the professionals have used the machine translation and 18% perform a proofreading.
- 2010: 28% of internet users, have used the machine translation and 50% planning to do.

3 Architectures of machine translation systems

Different strategies have been adopted by different researchers at different times in the history of machine translation. The choice of strategy reflects one side of the depth and linguistic diversity but also the grandeur of ambition on the other side. There are generally two types of architecture for machine translation, which are:

3.1 Linguistic Architecture

In the linguistic architecture there are three basic approaches being used for developing MT systems that differ in their complexity and sophistication. These approaches are:

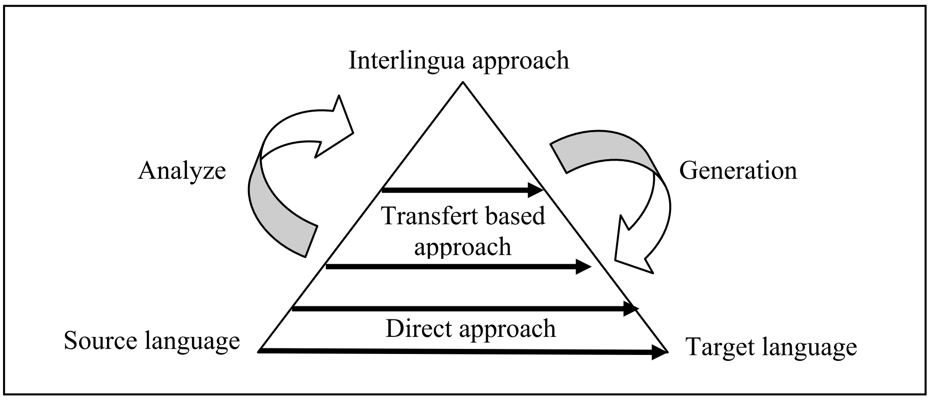

Fig1. The Vauquois triangle

- **Direct approach:** In direct translation, translation is direct from the source text to the target text. The vocabularies of SL texts are analyzed as needed for the resolution of SL ambiguities, for the correct identification of TL expressions as well as for the specification of word order in TL. This approach involves taking a string of words from the source language, removing the morphological

inflection from words to obtain the base forms, and looking them up in a bilingual dictionary between the source and the target languages. Components of this system are a large bilingual dictionary and a program for lexically and morphologically analyzing and generating texts [13].

- **Transfer-based approach:** In the Transfer approach, translation is completed through three stages: the first stage consists in converting SL texts into an intermediate representation, usually parse trees; the second stage converting these representations into equivalent ones in the target language; and the third one is the generation of the final target text [13].

  In the transfer approach, the source text is analyzed into an abstract representation that still has many of the characteristics of the source, but not the target, language. This representation can range from purely syntactic to highly semantic. In the syntactic transfer, some type of tree manipulation into a target language tree converts the parse tree of the source input. This can be guided by associating feature structures with the tree. Whatever representation is used, transfer to the target language is done using rules that map the source language structures into their target language equivalents. Then in the generation stage, the mapped target structure is altered as required by the constraints of the target language and the final translation is produced.
- **Interlingua approach:** The Interlingua approach is the most suitable approach for multilingual systems. It has two stages: Analysis (from SL to the Interlingua) and Generation (from the Interlingua to the TL). In the analysis phase, a sentence in the source language is analyzed and then its semantic content is extracted and represented in the Interlingua form representation, where an Interlingua is an entirely new language that is independent of any source or target language and is designed to be used as an intermediary internal representation of the source text. The analysis phase is followed by the generation of the target sentences from the Interlingua representation. An analysis program for a specific SL can be used for more than one TL since it is SL-specific and not oriented to any particular TL. Furthermore, the generation program for a particular TL can be used again for translation from every SL to this particular TL since it is TL-specific and not designed for input from a particular SL [13].

3.2 Computational Architecture

- **Rule Based approach:** rule-based MT has two approaches: Interlingua and transfer. Rule-Based MT Systems rely on different levels of linguistic rules for translation. This MT research paradigm has been named rule-based MT due to the use of linguistic rules of diverse natures. For instance, rules are used for lexical transfer, morphology, syntactic analysis, syntactic generation, etc. In RBMT the translation process consists of:
  - Analyzing input text morphologically, syntactically and semantically.
  - Generating text via structural conversions based on internal structures.

The steps mentioned above make use of a dictionary and a grammar, which must be developed by linguists. This requirement is the main problem of RBMT as it is a time-consuming process to collect and spell out this knowledge, frequently referred as knowledge acquisition problem. It is not just very hard to develop and maintain the rules in this type of system, but one is not guaranteed to get the system to operate as well as before the addition of a new rule. RBMT systems are large-scale rule based systems; whereas their computational cost is high, since they must implement all aspects whether syntactic, semantic, structural transfer etc. as rules [14].

- **Corpus-based approach:** Corpus-Based Machine Translation, also referred as data driven machine translation, is an alternative approach for machine translation to overcome the knowledge acquisition problem of rule-based machine translation. There are two types of CBMT Statistical Machine Translation (SMT) and Example-Based Machine Translation (EBMT). Corpus-based MT automatically acquires the translation knowledge or models from bilingual corpora. Since this approach has been designed to work on large sizes of data, it has been named Corpus-Based MT ([17], [18], [16] and [15]).
- **Hybride approach:** Some recent work has focused on hybrid approaches that combine the transfer approach with one of the corpus–based approaches. This was designed to work with fewer amounts of resources and depend on the learning and training of transfer rules. The main idea in this approach is to automatically learn syntactic transfer rules from limited amounts of word-aligned data. This data contains all the needed information for parsing, transfer, and generation of the sentences ([19] and [20]). The following section covers part of the MT literature that gives details of specific systems for deriving the appropriate translation using different approaches.

4 Types of Machine Translation

4.1 Machine Translation for Watcher (MT-W)

This is intended for readers who wanted to gain access to some information written in foreign language who are also prepared to accept possible bad translation rather than nothing. This was the type of MT envisaged by the pioneers. This came in with the need to translate military technological documents. This was almost the dictionary-based translation far away from linguistic based machine translation [25].

4.2 Machine Translation for Revisers (MT-R)

This type aims at producing raw translation automatically with a quality comparable to that of the first drafts produced by human. The translation output can be considered only as brush-up so that the professional translator freed from that very boring and time consuming task can be promoted to revisers [25].

4.3 Machine Translation for Translators (MT-T)

This aims at helping human translators do their job by providing on-line dictionaries, thesaurus and translation memory. This type of machine translation system is usually incorporated into the translation work stations and the PC based translation tools. “Tools for individual translators have been available since the beginning of office automation.” And those systems running on standard platforms and integrated with several text processors are the ones that attained operational and commercial success [25].

4.4 Machine Translation for Authors (MT-A)

This aims at authors wanting to have their texts translated into one or several languages and accepting to write under control of the system or to help the system disambiguate the utterance so that satisfactory translation can be obtained without any revision. This is an “interactive MT, The interaction was however done both during analysis and during transfer, and not by authors, but by specialists of the system and language(s).” In short, there have been no operational successes yet in MT-A, but the designs are becoming increasingly user oriented and geared towards the right kind of potential users, people users, people needing to produce translations, preferably into several languages [25].

5 Evaluation of Machine Translation Systems

Evaluating Machine translation system is important not only for its potential users and buyers, also to researchers and developers. Various types of evaluation have been developed, such as :

5.1 BLEU (BiLingual Evaluation Understudy)

The BLEU metric, proposed by Papineni in 2001 was the first automatic measurement accepted as a reference for the evaluation of translations. The principle of this method is to calculate the degree of similarity between candidate (machine) translation and one or more reference translations based on the particular n-gram precision. The BLEU score is defined by the following formula [21]:

$$\text{BLEU} = \text{BP} \times e^{\left(\sum_{n=1}^{N} w_i \log pn\right)} \quad (1)$$

Where:

- “pn”: the number of n-grams of machine translation is also present in one or more reference translation, divided by the number of total n-grams of machine translation.
- “w_i”: positive weights.

- "BP": Brevity Penalty, which penalizes translations for being "too short". The brevity penalty is computed over the entire corpus and was chosen to be a decaying exponential in "r/c", where "c" is the length of the candidate translation and "r" is the effective length of the reference translation.

$$BP = \begin{cases} 1 & \text{Si} \quad c > r \\ e^{1-\frac{r}{c}} & \text{Si} \quad c \leq r \end{cases} \qquad (2)$$

5.2 WER (Word Error Rate)

The WER metric, Proposed by Popovic and Ney in 2007. Originally used in Automatic Speech Recognition, compares a sentence hypothesis refers to a sentence based on the Levenshtein distance. It is also used in machine translation to evaluate the quality of a translation hypothesis in relation to a reference translation. For this, the idea is to calculate the minimum number of edits (insertion, deletion or substitution of the word) to be performed on hypothesis translation to make it identical to the reference translation. The number of editss to be performed, noted "d_L(ref, hyp)" is then divided by the size of the reference translation, denoted "N_{ref}" as shown in the following formula [22]:

$$WER = \frac{1}{N_{ref}} \text{ x } d_L(\text{ref, hyp}). \qquad (3)$$

Where:

- d_L(ref, hyp): is the Levenshtein distance between the reference translation "ref" and the hypothesis tanslation "hyp".

A shortcoming of the WER is the fact that it does not allow reordering of words, whereas the word order of the hypothesis can be different from word order of the reference even though it is correct translation.

5.3 PER (Position-independent word Error Rate)

The PER metric, proposed by Tillman in 1997. compare the words of machine translation with those of the reference regardless of their sequence in the sentence. The PER score is defined by the following formula [23]:

$$PER = \frac{1}{N_{ref}} \text{x } d_{per}(\text{ref, hyp}). \qquad (4)$$

Where:

- d_{per}: calculates the difference between the occurrences of words in machine translation and the translation of reference.

A shortcoming of the PER is the fact that the word order can be important in some cases.

5.4 TER (Translation Error Rate)

The TER metric, proposed by Snover in 2006. Is defined as the minimum number of edits needed to change a hypothesis so that it exactly matches one of the references. The possible edits in TER include insertion, deletion, and substitution of single words, and an edit which moves sequences of contiguous words. Normalized by the average length of the references. Since we are concerned with the minimum number of edits needed to modify the hypothesis, we only measure the number of edits to the closest reference. The TER score is defined by the following formula [24]:

$$\text{TER}=\frac{Nb\ (op)}{AvregN_{\ Ref}} \qquad (5)$$

Where:

- Nb (op) : is the minimum number of edits;
- Avreg N_{ref}: the average size in words references.

6 Conclusion

In conclusion, we can say that the field of machine translation has been and remains a key focus of research on natural language processing and that led to the development of many positive results. However, perfection is still far away. If the translators have today reached a level of reliability and efficiency in a technical text, perfection is still a long way in the literary text, overwhelmed by the intricacies, the puns and colorful expressions. We think it must look to the construction of a translator hybrid (combining statistical and rules) at the end to increase the performance of the translation system.

References

1. Hutchins, W. J. and Somers, H. L., An introduction to machine translation, Academic Press, London. (1992)
2. Baumgartner-Bovier, “ La traduction automatique, quel avenir ? Un exemple basé sur les mots composés ”, Cahiers de Linguistique Française N°25, (2003).
3. J. Chandioux, “Histoire de la traduction automatique au Canada”, journal des traducteurs, vol. 22, n° 1, p. 54-56, (1977).
4. H. Kaji, “HICATS/JE : A Japanese-to-English Machine Translation System Based on Semantics ”, Machine Translation Summit, (1987).
5. Y. Lepage, E. Denoual, “ALEPH: an EBMT system based on the preservation of proportional analogies between sentences across languages ”, (2005).
6. Y. Fukumochi, “A Way of Using a Small MT System in Industry ”, the 5th Machine Translation Summit, July 10-13, (1995).